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The Impact of Digital Economy Development on Chinese Firms Performance

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Abstract

This study examines the dynamic and asymmetric effects of digital economy development on firm performance in China using annual time-series data spanning 2002 to 2024. Internet penetration rate is adopted as the primary proxy for digital economy development, while the aggregate Return on Assets (ROA) of Chinese A-share listed companies serves as the measure of firm performance. Employing the Autoregressive Distributed Lag (ARDL) and Nonlinear Autoregressive Distributed Lag (NARDL) frameworks, this study investigates both the long-run equilibrium relationship and short-run dynamic adjustment between these variables. The ARDL bounds test confirms the existence of a stable cointegrating relationship at the 1% significance level. The estimated long-run coefficient of digital economy development is 1.821, indicating that a 1% increase in internet penetration rate is associated with an approximate 0.018 percentage-point increase in aggregate firm ROA. The short-run coefficient (8.232) substantially exceeds the long-run estimate, demonstrating that the immediate impact of digital economy shocks is considerably more pronounced than the equilibrium effect. The error correction term coefficient (−0.800) is statistically significant, implying that approximately 80% of any short-run deviation is corrected within one year. The NARDL exploratory analysis does not confirm statistically significant asymmetric effects, reflecting the trajectory of uninterrupted digital expansion in China during the sample period. Robustness checks using an alternative proxy confirm the stability of the core findings. These results offer both theoretical insights and practical implications for digital infrastructure policy and corporate digital transformation strategies in emerging economies.

Keywords

Digital economy; Firm performance; ARDL; NARDL; Internet penetration; China

1. Introduction

The rapid development of the digital economy has emerged as a defining feature of contemporary economic transformation, reshaping production processes, business models, and competitive dynamics across all major sectors. In China, the digital economy expanded to 59.5 trillion yuan in 2024, accounting for 42.5% of gross domestic product (CAICT, 2023), underscoring the central role that digital technologies now play in the country's economic structure. Against this backdrop, understanding how digital economy development shapes firm performance has become a critical question for both academic research and policy practice.

From a theoretical perspective, digital technologies reduce transaction costs, alleviate information asymmetries, enhance resource allocation efficiency, and facilitate innovation (Coase, 1937; Williamson, 2010; Teece et al., 1997). However, the empirical literature presents mixed evidence. While numerous studies document a positive relationship between digitalization and firm performance (Zhang et al., 2022; Liu & Li, 2023; Wu et al., 2021), others identify potential negative effects, including digital transformation traps, high adoption costs, and organizational inertia (Chen, 2024; Warner & Wäger, 2019). This divergence suggests that the relationship between digital economy development and firm performance is neither simple nor linear.

A more fundamental methodological limitation in the existing literature concerns the predominance of static linear panel models, which are inadequate for capturing the dynamic adjustment process inherent in digital transformation. Firm performance does not respond instantaneously to changes in the digital environment; rather, adjustment involves learning processes, capability accumulation, and organizational restructuring that unfold gradually over time. Moreover, firms may respond asymmetrically to positive and negative shocks in digital economy development, a feature that conventional symmetric models fail to accommodate (Shin, Yu, & Greenwood-Nimmo, 2014).

To address these gaps, this study employs the ARDL and NARDL frameworks using national-level time-series data for China from 2002 to 2024. The ARDL model (Pesaran, Shin, & Smith, 2001) allows for the simultaneous estimation of short-run dynamics and long-run equilibrium effects and is particularly suitable for small samples with variables integrated of mixed orders. The NARDL extension tests whether positive and negative changes in the digital economy exert asymmetric effects on firm performance.

This study is guided by three research objectives: (1) to test the overall impact of digital economy development on firm performance; (2) to distinguish between short-run fluctuations and long-run equilibrium effects; and (3) to analyze potential asymmetric responses to positive and negative digital economy shocks. The findings contribute a dynamic, time-series perspective to a literature dominated by cross-sectional and static panel approaches, and provide empirical evidence for digital economy policy design in China and analogous emerging economies.

2. Methodology

2.1 Data and Variable Construction

This study employs annual national-level time-series data for China covering the period 2002 to 2024, yielding 23 observations. The sample period encompasses the key stages of China's digital transformation, from the early diffusion of internet infrastructure to the widespread deployment of advanced digital technologies.

The dependent variable is firm performance, measured by the annual average Return on Assets (ROA) of Chinese A-share listed companies. Firm-level financial data are sourced from the China Stock Market and Accounting Research (CSMAR) database. Following standard practice, firms classified as ST or *ST and those in the financial sector are excluded. The core independent variable is digital economy development, proxied by internet penetration rate—the proportion of internet users in the total population—transformed using the natural logarithm (LnDE). Data are sourced from the China Internet Network Information Center (CNNIC) and the National Bureau of Statistics (NBS). GDP growth rate (GDPG) is included as a control variable to isolate the net effect of digital economy development from business cycle fluctuations.

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2.2 Unit Root Tests

The stationarity of all variables is examined using the Augmented Dickey-Fuller (ADF) test and the Phillips-Perron (PP) test. Both tests evaluate the null hypothesis of a unit root. The ARDL framework requires that no variable is integrated of order two, I(2).

2.3 ARDL Bounds Test and Error Correction Model

The ARDL model (Pesaran et al., 2001) is employed to test for cointegration and to estimate long-run and short-run relationships simultaneously. The model is specified as an unrestricted error correction model:

$$\begin{aligned}\Delta ROA_t = \; & \alpha_0 + \sum_{i=1}^{p} \alpha_{1i}\, \Delta ROA_{t-i} + \sum_{j=0}^{q_1} \alpha_{2j}\, \Delta LnDE_{t-j} + \sum_{k=0}^{q_2} \alpha_{3k}\, \Delta GDPG_{t-k} \\ & + \sum_{l=0}^{q_3} \alpha_{4l}\, \Delta FAIG_{t-l} + \beta_1 ROA_{t-1} + \beta_2 LnDE_{t-1} + \beta_3 GDPG_{t-1} \\ & + \beta_4 FAIG_{t-1} + \epsilon_t \end{aligned} \quad (1)$$

The optimal lag structure is selected using the Akaike Information Criterion (AIC). Cointegration is assessed via the bounds testing procedure, which evaluates the joint significance of the lagged level terms (β_1, β_2, β_3). If the F-statistic exceeds the upper critical bound, the null hypothesis of no cointegration is rejected. Once cointegration is confirmed, short-run dynamics are captured through the Error Correction Model (ECM):

$$\begin{aligned}\Delta ROA_t = \; & \alpha_0 + \sum_{i=1}^{p-1} \alpha_{1i}\, \Delta ROA_{t-i} + \sum_{j=0}^{q_1-1} \alpha_{2j}\, \Delta LnDE_{t-j} \\ & + \sum_{k=0}^{q_2-1} \alpha_{3k}\, \Delta GDPG_{t-k} + \sum_{l=0}^{q_3-1} \alpha_{4l}\, \Delta FAIG_{t-l} \\ & + \lambda ECT_{t-1} + \epsilon_t \end{aligned} \quad (2)$$

where $ECT_{(t-1)}$ is the lagged error correction term, and λ captures the speed of adjustment toward long-run equilibrium. A negative and statistically significant λ confirms the stability of the long-run relationship.

2.4 NARDL Model for Asymmetric Analysis

To investigate whether positive and negative changes in digital economy development exert differential effects on firm performance, the NARDL model (Shin et al., 2014) is employed. The explanatory variable is decomposed into positive and negative partial sum components:

$$LnDE_t^{+} = \sum_{j=1}^{t} \Delta\, LnDE_j^{+} = \sum_{j=1}^{t} max\,(\Delta LnDE_j, 0) \quad (3)$$

$$LnDE_t^{-} = \sum_{j=1}^{t} \Delta\, LnDE_j^{-} = \sum_{j=1}^{t} min\,(\Delta LnDE_j, 0) \quad (4)$$

Based on this decomposition, the NARDL model is specified as:

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$$\Delta ROA_t = \alpha_0 + \sum_{i=1}^{p} \alpha_{1i}\,\Delta ROA_{t-i} + \sum_{j=0}^{q_1} (\beta_j^{+}\Delta LnDE_{t-j}^{+} + \beta_j^{-}\Delta LnDE_{t-j}^{-}) + \sum_{k=0}^{q_2} \alpha_{3k}\,\Delta GDPG_{t-k} + \sum_{l=0}^{q_3} \alpha_{4l}\,\Delta FAIG_{t-l} + \rho_1 ROA_{t-1} + \rho_2^{+} LnDE_{t-1}^{+} + \rho_2^{-} LnDE_{t-1}^{-} + \rho_3 GDPG_{t-1} + \rho_4 FAIG_{t-1} + \epsilon_t \quad (5)$$

where $\theta^+ = -\rho_2{}^+/\rho_1$ and $\theta^- = -\rho_2{}^-/\rho_1$ represent the long-run effects of positive and negative digital economy shocks, respectively. Long-run asymmetry is formally tested using a Wald test of H_0: $\theta^+ = \theta^-$. Since the primary proxy—internet penetration rate—follows a strictly monotonic increasing path throughout the sample period and cannot be decomposed into positive and negative partial sums, the asymmetric analysis employs internet users (LnDE_robust) as an alternative proxy.

3. Results and Discussion

3.1 Descriptive Statistics

Table 1 summarizes the descriptive statistics for the three variables over the sample period 2002–2024.

Table 1: Descriptive Statistics

Variable	Obs.	Mean	Median	Std. Dev.	Min.	Max.
ROA%	23	5.633	5.856	1.439	3.228	9.140
LnDE	23	3.454	3.824	0.903	1.526	4.364
GDPG	23	8.183	7.900	2.842	2.300	14.20

ROA has a sample mean of 5.63% and a median of 5.86%, indicating a relatively symmetric distribution. The standard deviation of 1.44% reflects moderate dispersion across the sample period. The digital economy indicator LnDE exhibits wide variation, corresponding to an underlying internet penetration rate that rose continuously from 4.6% in 2002 to 78.6% in 2024. GDP growth averaged 8.18%, with a maximum of 14.20% in 2007 and a minimum of 2.30% in 2020, the latter reflecting the impact of the COVID-19 pandemic.

3.2 Unit Root Tests

The results of the ADF and PP unit root tests are reported in Table 2.

Table 2: Unit Root Test Results

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Variable	ADF (Level)	ADF (1st Diff.)	PP (Level)	PP (1st Diff.)	Conclusion
ROA	−2.779 (0.078)	−5.971*** (0.000)	−2.759 (0.081)	−6.938*** (0.000)	I(1)
LnDE	−4.152*** (0.005)	—	−4.181*** (0.004)	—	I(0)
LnDE robust	−4.769*** (0.001)	—	−4.158*** (0.004)	—	I(0)
GDPG	−0.804 (0.797)	−3.389** (0.025)	−1.700 (0.417)	−11.476*** (0.000)	I(1)

LnDE and LnDE rubust are stationary in levels at the 1% significance level, classified as I(0). ROA and GDPG fail to reject the unit root null hypothesis in levels but become stationary after first differencing, classified as I(1). No variable is I(2), satisfying the precondition for ARDL estimation. The ADF and PP tests yield consistent conclusions, confirming the robustness of these results.

3.3 ARDL Bounds Cointegration Tests

The optimal ARDL specification, selected by the Akaike Information Criterion, is ARDL(1, 1, 0). Table 3 reports the results of the bounds cointegration test.

Table 3: ARDL Bounds Cointegration Test

Significance Level	I(0) Bound	I(1) Bound
10%	2.915	3.695
5%	3.538	4.428
1%	5.155	6.265
F-statistic = 6.347*** (k = 2)		

The F-statistic of 6.347 exceeds the upper bound critical value of 6.265 at the 1% significance level, rejecting the null hypothesis of no cointegration. A stable long-run equilibrium relationship exists among ROA, LnDE, and GDPG, confirming that the observed co-movement is not a spurious short-run coincidence. This finding provides the empirical foundation for subsequent long-run and short-run estimation.

3.4 Long-Run Equilibrium and Short-Run Dynamics

Table 4 presents the estimated long-run coefficients and error correction model from the ARDL(1, 1, 0) specification.

Table 2: Unit Root Test Results

	Variable	Coefficient	Std. Error	t-Statistic	Prob.
Long-Run	Ln DE	1.821***	0.595	3.063	0.006

	GDPG	0.398**	0.178	2.234	0.038
	Constant	−5.077	3.242	−1.566	0.134
Short-Run	COINTEQ(−1)	−0.800***	0.146	−5.465	0.000
	D(Ln DE)	8.232***	1.692	4.866	0.000

In the long run, the coefficient of LnDE is 1.821 and is statistically significant at the 1% level (p = 0.006). A 1% increase in the internet penetration rate raises aggregate firm ROA by approximately 0.018 percentage points in long-run equilibrium. This result confirms Hypothesis 1—digital economy development significantly and positively affects firm performance. The positive effect is consistent with the theoretical prediction that digital technologies reduce transaction costs, improve information processing efficiency, and enhance firms' resource allocation capabilities (Williamson, 2010; Brynjolfsson & Hitt, 2000). The long-run coefficient of GDP growth (0.398, p = 0.038) confirms the importance of macroeconomic conditions in supporting corporate profitability.

The short-run coefficient of D(LnDE) is 8.232, significant at the 1% level (p = 0.000). This estimate substantially exceeds the long-run coefficient of 1.821. The pronounced divergence between short-run and long-run effects supports Hypothesis 2, indicating that the immediate impact of digital economy changes on firm performance is considerably more intense than the equilibrium effect. In the short run, firms may experience amplified responses due to adjustment costs, organizational pressures, and technology assimilation challenges. Over time, as firms complete the adaptation process and absorb the shock, the effect converges to the more moderate long-run level.

The error correction term COINTEQ(−1) has a coefficient of −0.800, highly significant at the 1% level (p = 0.000). This negative and significant coefficient confirms the existence and stability of the long-run equilibrium relationship. The magnitude implies that approximately 80% of any short-run deviation from equilibrium is corrected within one year, indicating a strong self-adjustment mechanism. This high correction speed reflects the relatively rapid responsiveness of China's listed companies to changes in the digital economic environment.

3.5 Model Diagnostic Tests

Table 5 summarizes the results of diagnostic tests performed on the ARDL model residuals.

Table 5: Diagnostic Test Results

Test	Statistic	p-value	Decision
Breusch-Godfrey LM (2 lags)	F = 1.293	0.304	No serial correlation
ARCH (1 lag)	F = 1.656	0.214	No heteroskedasticity
Jarque-Bera	JB = 1.096	0.578	Normally distributed
CUSUM stability	—	—	Parameters stable

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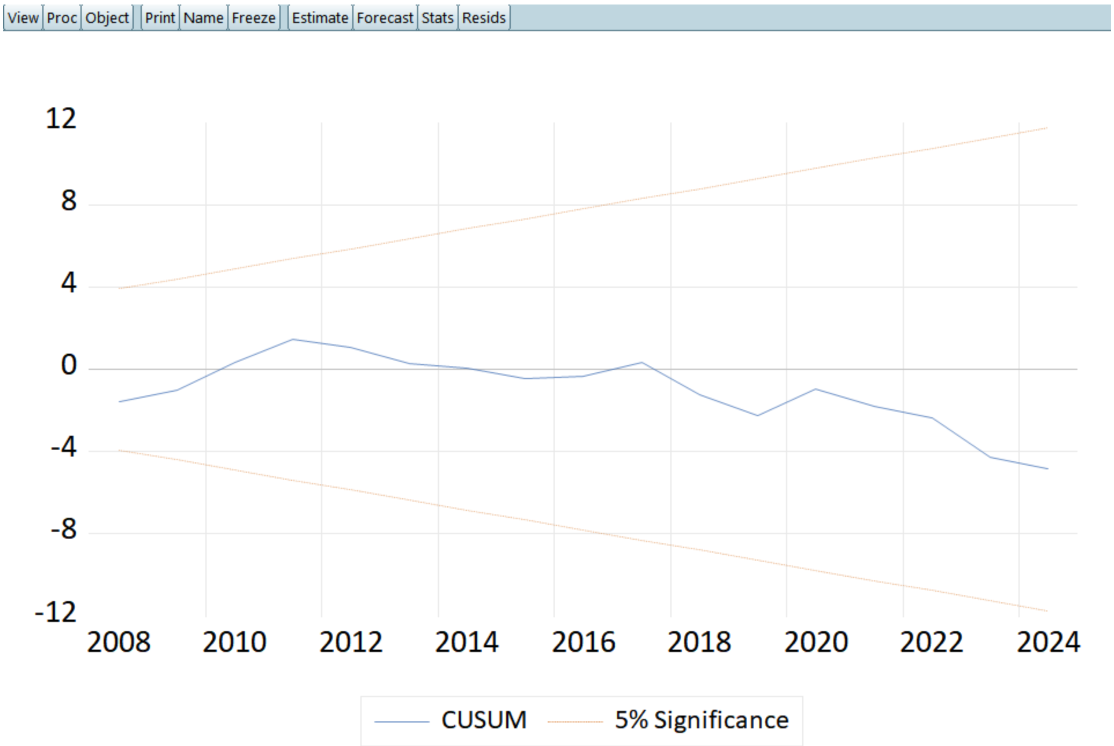
Figure 1 illustrates the parameter stability is further confirmed by the CUSUM test. As shown in Figure 1, the cumulative sum of recursive residuals remains within the 5% significance boundaries throughout the entire sample period, providing no evidence of structural breaks in the estimated parameters.model.

Fig. 1. CUSUM Stability Test of the ARDL Model.



All four diagnostic tests are passed. The residuals exhibit no evidence of serial correlation, heteroskedasticity, or non-normality, and the CUSUM stability test confirms that model parameters remain structurally stable throughout the entire sample period. The ARDL estimates therefore rest on a sound econometric foundation.

3.6 Asymmetric Effects: NARDL Analysis

As discussed in the methodology, the primary proxy—internet penetration rate—follows a strictly monotonic increasing path throughout the sample period and cannot be decomposed into positive and negative partial sums. Accordingly, the NARDL analysis employs internet users (LnDE_robust) as the alternative proxy. The optimal NARDL specification is ARDL(1, 0, 1). The estimated long-run coefficient for positive digital shocks (LnDE_robust_POS) is 1.810 (p = 0.014), while the coefficient for negative shocks (LnDE_robust_NEG) is 13.841 (p = 0.204). Despite the large numerical difference, the

Wald test for long-run asymmetry yields an F-statistic of 1.393 ($p = 0.256$), failing to reject the null hypothesis of symmetry. Hypothesis 3 is therefore not supported under the current data conditions.

This result does not negate the theoretical possibility of asymmetric adjustment. Rather, it reflects the defining empirical characteristic of China's digital economy during the sample period: a trajectory of continuous and uninterrupted expansion. The negative partial sum variable exhibits minimal sample variation, resulting in large estimation uncertainty for the negative shock coefficient. As Pan et al. (2022) and Mouna and Yassine (2024) note, infrastructure-based proxies in rapidly developing economies tend to follow monotone trends that limit the power of asymmetry tests. Should significant negative shocks materialize in the future—through regulatory disruptions, technological reversals, or infrastructure saturation—the empirical basis for identifying asymmetric effects would improve substantially.

3.7 Robustness Check

To verify that the core findings are not sensitive to the choice of proxy, the baseline ARDL model is re-estimated using internet users (LnDE_robust). Table 6 compares the key estimates across the baseline and robustness specifications.

Table 6: Comparison of Baseline and Robustness Results.

	Baseline (LnDE)	Robustness (LnDE_robust)
Digital Economy (LR)	1.821***	1.676***
GDP Growth (LR)	0.398**	0.438**
COINTEQ(−1)	−0.800***	−0.815***
Bounds F-statistic	6.347	6.075

The long-run digital economy coefficient shifts modestly from 1.821 to 1.676, remaining positive and significant at the 1% level. The GDP growth coefficient (0.438) and the error correction term (−0.815) are also closely consistent with the baseline estimates. The bounds test confirms cointegration at the 5% level ($F = 6.075$), and all diagnostic tests are passed. The structural pattern—wherein the short-run impact substantially exceeds the long-run equilibrium effect—is fully preserved in the robustness model. These results confirm that the core conclusions do not depend on the choice of a specific digital economy indicator.

4. Conclusion

This study employs ARDL and NARDL time-series frameworks to examine the dynamic and asymmetric effects of digital economy development on aggregate firm performance in China over the period 2002–2024. Three principal conclusions emerge.

First, digital economy development exerts a significant and positive long-run effect on firm performance. The ARDL bounds test confirms a stable cointegrating relationship at the 1% significance level. The long-run coefficient of internet penetration rate is 1.821, indicating that a 1% increase in penetration raises aggregate firm ROA by approximately 0.018 percentage points after controlling for macroeconomic conditions. This finding is consistent with transaction cost theory and resource-based perspectives, confirming that broader digital infrastructure enhances information processing efficiency, reduces coordination costs, and facilitates innovation.

Second, the impact of digital economy development on firm performance exhibits a significant structural difference between the short run and the long run. The short-run coefficient (8.232) is substantially larger than the long-run equilibrium estimate (1.821), reflecting the amplified initial response arising from adjustment pressures and organizational adaptation costs. The error correction coefficient (−0.800) is highly significant, indicating that approximately 80% of any deviation from long-run equilibrium is corrected within one year—a rapid adjustment speed consistent with the dynamism of China's listed-company sector.

Third, statistically significant asymmetric effects cannot be confirmed under the current data conditions. The Wald test in the NARDL framework fails to reject long-run symmetry. This result does not contradict the theoretical expectation of asymmetric firm responses; rather, it reflects the empirical reality that China's digital infrastructure experienced uninterrupted expansion during the sample period, without negative shocks of sufficient magnitude to support asymmetric identification.

Based on these findings, several policy recommendations are proposed. Digital infrastructure investment should be sustained and deepened, particularly in bridging regional and rural-urban digital divides, as broad internet penetration generates lasting corporate performance improvements. Policymakers should also account for the pronounced short-run adaptation pressures that accompany digital technology adoption by providing phased support mechanisms—such as technical subsidies and transition allowances—to help firms absorb initial adjustment costs. As infrastructure penetration approaches saturation, policy emphasis should shift from expanding network coverage toward deepening data utilization and advancing industrial digitalization. Finally, maintaining macroeconomic stability is a prerequisite for enabling firms to fully realize the productivity dividends of digital economy development, as confirmed by the consistently positive and significant long-run effect of GDP growth.

This study has several limitations. First, reliance on infrastructure-based proxies may not fully capture the breadth of the digital economy, including industrial digitalization and digital governance dimensions. Second, the 23-year sample period, while suitable for ARDL estimation, limits the complexity of feasible model specifications. Third, aggregating firm performance to the national level masks heterogeneity across industries, ownership types, and firm sizes. Future research should consider constructing comprehensive time-series digital economy indices, employing longer data series as they become available, and investigating firm-level heterogeneity through panel time-series methods.

References

1. Barefoot, K., Curtis, D., Jolliff, W., Nicholson, J. R., & Omohundro, R. (2018). Defining and measuring the digital economy. US Department of Commerce Bureau of Economic Analysis, 15(2).
2. Brynjolfsson, E., & Hitt, L. M. (2000). Beyond computation: Information technology, organizational transformation and business performance. Journal of Economic Perspectives, 14(4), 23–48.
3. Chen, X., Zhang, X. E., Cai, Z., & Chen, J. (2024). The non-linear impact of digitalization on the performance of SMEs. Systems, 12(4), 139.
4. China Academy of Information and Communications Technology. (2023). Report on China's Digital Economy Development. CAICT.
5. Coase, R. H. (1937). The nature of the firm. Economica, 4(16), 386–405.
6. Dickey, D. A., & Fuller, W. A. (1981). Likelihood ratio statistics for autoregressive time series with a unit root. Econometrica, 49(4), 1057–1072.

7. Hess, T. (2019). Digitale Transformation strategisch steuern. Springer-Verlag.
8. Liu, H., & Li, S. (2023). The impact of urban digital economy development on manufacturing innovation efficiency. International Journal of Empirical Economics, 2(02), 2350004.
9. Ma, L. F., Thanaphon, R., & Gumpora, S. (2024). Research on the impact of digital transformation on the performance of manufacturing enterprises. Proceedings of Business and Economic Studies, 7(4), 16–22.
10. Mouna, B., & Yassine, M. (2024). Business leadership in e-commerce in the USA: The impact of blockchain technology. Business Ethics and Leadership, 8(1), 116–128.
11. Pan, W., Xie, T., Wang, Z., & Ma, L. (2022). Digital economy: An innovation driver for total factor productivity. Journal of Business Research, 139, 303–311.
12. Pesaran, M. H., Shin, Y., & Smith, R. J. (2001). Bounds testing approaches to the analysis of level relationships. Journal of Applied Econometrics, 16(3), 289–326.
13. Phillips, P. C., & Perron, P. (1988). Testing for a unit root in time series regression. Biometrika, 75(2), 335–346.
14. Richard, P. J., Devinney, T. M., Yip, G. S., & Johnson, G. (2009). Measuring organizational performance: Towards methodological best practice. Journal of Management, 35(3), 718–804.
15. Shin, Y., Yu, B., & Greenwood-Nimmo, M. (2014). Modelling asymmetric cointegration and dynamic multipliers in a nonlinear ARDL framework. In Festschrift in Honor of Peter Schmidt (pp. 281–314). Springer.
16. Syverson, C. (2011). What determines productivity? Journal of Economic Literature, 49(2), 326–365.
17. Teece, D. J., Pisano, G., & Shuen, A. (1997). Dynamic capabilities and strategic management. Strategic Management Journal, 18(7), 509–533.
18. Wan, M. (2025). Organizational inertia and digital transformation outcomes: Evidence from Chinese enterprises.
19. Warner, K. S., & Wäger, M. (2019). Building dynamic capabilities for digital transformation. Long Range Planning, 52(3), 326–349.
20. Williamson, O. E. (2010). Transaction cost economics: The natural progression. American Economic Review, 100(3), 673–690.
21. Wu, F., Hu, H., Lin, H., & Ren, X. (2021). Enterprise digital transformation and capital market performance. Management World, 37(7), 130–144.
22. Zhang, T., Shi, Z. Z., Shi, Y. R., & Chen, N. J. (2022). Enterprise digital transformation and production efficiency. Economic Research–Ekonomska istraživanja, 35(1), 2781–2792.
23. Zhou, Z., Liu, W., Cheng, P., & Li, Z. (2022). The impact of the digital economy on enterprise sustainable development. Sustainability, 14(19), 11948.